



## Spatial modelling approach and accounting method affects soil carbon estimates and derived farm-scale carbon payments

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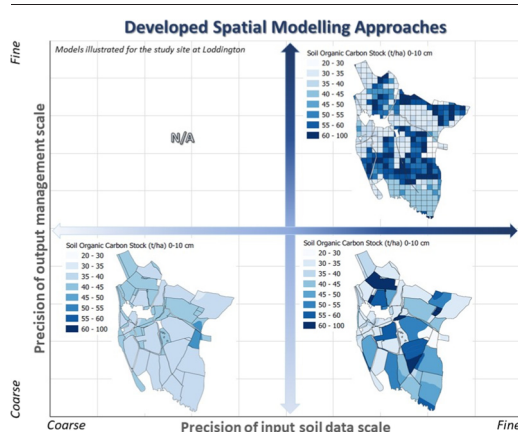
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### HIGHLIGHTS

- SOC field estimates derived from national datasets depend on the modelling approach.
- Models with fine scale input data provide more robust SOC estimates at field-level.
- A fine input and output model can assist farmers adjust their management practices.
- Estimated baseline payments derived by the tested models favour farms with high SOC.
- Farms with low SOC are unfavoured by models to predict their initial baseline.

### GRAPHICAL ABSTRACT



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### ABSTRACT

Improved farm management of soil organic carbon (SOC) is critical if national governments and agricultural businesses are to achieve net-zero targets. There are opportunities for farmers to secure financial benefits from carbon trading, but field measurements to establish SOC baselines for each part of a farm can be prohibitively expensive. Hence there is a potential role for spatial modelling approaches that have the resolution, accuracy, and estimates to uncertainty to estimate the carbon levels currently stored in the soil. This study uses three spatial modelling approaches to estimate SOC stocks, which are compared with measured data to a 10 cm depth and then used to determine carbon payments. The three approaches used either fine- (100 m × 100 m) or field-scale input soil data to produce either fine- or field-scale outputs across nine geographically dispersed farms. Each spatial model accurately predicted SOC stocks (range: 26.7–44.8 t ha<sup>-1</sup>) for the five case study farms where the measured SOC was lowest (range: 31.6–48.3 t ha<sup>-1</sup>). However, across the four case study farms with the highest measured SOC (range: 56.5–67.5 t ha<sup>-1</sup>), both models underestimated the SOC with the coarse input model predicting lower values (range: 39.8–48.2 t ha<sup>-1</sup>) than those using fine inputs (range: 43.5–59.2 t ha<sup>-1</sup>). Hence the use of the spatial models to establish a baseline, from which to derive payments for additional carbon sequestration, favoured farms with already high SOC levels, with that benefit greatest with the use of the coarse input data. Developing a national approach for SOC sequestration payments to farmers is possible but the economic impacts on individual businesses will depend on the approach and the accounting method.

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## 1. Introduction

To reduce the effects of climate change, many countries are implementing policies to achieve net-zero greenhouse gas (GHG) emissions by 2050 (Smith et al., 2012; Van Soest et al., 2021). A key policy measure in those countries is to incentivise land managers to sequester more soil carbon as some sectors of the economy will remain a source of GHG even in 2050 (Chambers et al., 2016). This planned increase in soil carbon will be in contrast to a previous historic global loss of soil carbon of about 133 Gt, primarily because of agricultural practices (FAO and ITPS, 2021). Globally it is estimated that about 1700 Gt of carbon is stored in the soil to a depth of 1 m (Canadell et al., 2021), although the mean estimates of 27 global studies have ranged from 504 Gt to 3000 Gt (Scharlemann et al., 2014).

Because increasing soil carbon storage can be a very effective climate change mitigation strategy (Amin et al., 2020), many national governments are planning to pay farmers to increase the amount of carbon stored on their land (e.g. UK Government, 2021a). There are two practical challenges that need to be addressed for this policy to be successful. Firstly, it is expensive to develop a robust soil C baseline from which to evaluate the success of C sequestration measures at farm level. Measurement of soil carbon in every field can be costly and measurements can vary widely within small areas due to the inherent soil variability. Secondly, the policy formulations around farmer incentives need to consider both the retention of existing soil C as well as encouraging farmers and land managers to sustainably increase soil C over the medium to long term. Hence, national incentivization schemes need to have means of producing robust, auditable information on the amount of current levels of soil C stored on farms, and an accounting procedure to quantify the amount of carbon that has been or will be sequestered.

The cost of using physical field measurements of SOC and bulk density to establish a baseline can be high, moreover, it may be more cost-effective to use spatial models. Such spatial models, and their underlying data sets, are often derived from national-level soil C datasets such as national soil maps (Veronesi et al., 2014). These need to be downscaled to farm, field and within field-level soil C estimates which are sufficiently robust, policy-relevant and useful for farmer decision making. Whereas there is a substantive body of research on national and international level soil C stocks (Adhikari et al., 2019; Bárcena et al., 2014; Chen et al., 2019; Guo and Gifford, 2002; Wang et al., 2018); and on site-specific and soil process-specific C sequestration processes (Baisden et al., 2002; Coleman et al., 2017; Laskar et al., 2021; Muhammed et al., 2018; Muhlbachova et al., 2015; Pschenyckyj et al., 2020), there is surprisingly little information on the implication of using national-level datasets at local, farm-level decision making, and the economic consequences of using different national datasets to support decisions at farm level. This study aims to prove the hypothesis that there are consequences concerning policy, payments and land users when national-level soil C information is downscaled to a farm and a field level. To test the hypothesis, three spatial modelling approaches were developed and compared to quantify SOC stocks and their associated uncertainty at a farm-scale. This was followed by an examination of how the modelling approach and accounting method for carbon payments could affect farm revenue and the societal cost of promoting carbon sequestration.

## 2. Materials and methods

### 2.1. Description of study areas and soils datasets

Existing measurements of SOC and bulk density were collated from nine locations to form a calibration and a validation dataset. The calibration dataset comprised SOC and bulk density data (0–10 cm) taken at five farms across Great Britain, following a method described by Hodson et al. (2021). The farms or sites were Hodgson's Fields near Skeffling in Yorkshire (SKF), the Allerton Project farm at Loddington, Leicestershire (LOD), Manor Farm near Bath in Somerset (MAN), Elm Farm Organic Research Centre in

Berkshire (ELM), and a farm near Swanage in Dorset (SWA). The validation dataset included another two sites described by Hodson et al. (2021): a site at Craibstone in Aberdeenshire (ABE) and Torr Organic Farm near Auchencairn in Dumfries and Galloway (TORR) (Fig. 1). The validation dataset also included SOC and bulk density obtained from Clapham Park and Silsoe in Bedfordshire (Upson, 2014). The site at Clapham Park comprised areas of 14-year-old woodland, grassland, and silvopasture agroforestry with widely-spaced trees planted on grassland (Upson et al., 2016). The site at Silsoe comprised an arable area that had recently been converted to grassland and an area of widely-spaced poplar trees with a grass understorey (Upson and Burgess, 2013). Soil samples were taken over a depth including 0–10 cm and analysed as described by Upson et al. (2016) and Upson and Burgess (2013).

### 2.2. Spatial modelling approaches

Three spatial modelling approaches were used to predict the SOC stock at the nine sites across four cardinal directions and to a soil depth of 10 cm. The three approaches included different combinations of two distinct sources of spatial soil data inputs and two output scales (Fig. 2). A depth of 10 cm was chosen because this was the depth available in the measured datasets used for the calibration and validation of the approaches (Table A.1 in Appendix A).

Many existing digital soil maps describe soil organic carbon at a relatively coarse scale of 1 km × 1 km. For example, in England and Wales, field surveys between 1979 and 1983 were used to create a national soils map (NATMAP) of soil associations, and a National Soil Inventory was made on a 5 km × 5 km grid describing soil properties such as soil organic content (Keay et al., 2009; Hallett et al., 2017). Using these two sources, and information from the National Soil Inventory of Scotland (NSIS) (Lilly et al., 2010), a map of SOC at a 1 km × 1 km scale was created for Great Britain (Bradley et al., 2005; Gregory et al., 2014). However, it is possible to use additional variables, such as meteorological data and altitude, and using random forest and artificial neural networks to determine the soil variability at a finer scale of 100 m × 100 m (Taalab et al., 2013). Using such techniques, Campbell (2018) developed a dataset of soil organic content for Great Britain using a 100 m × 100 m grid.

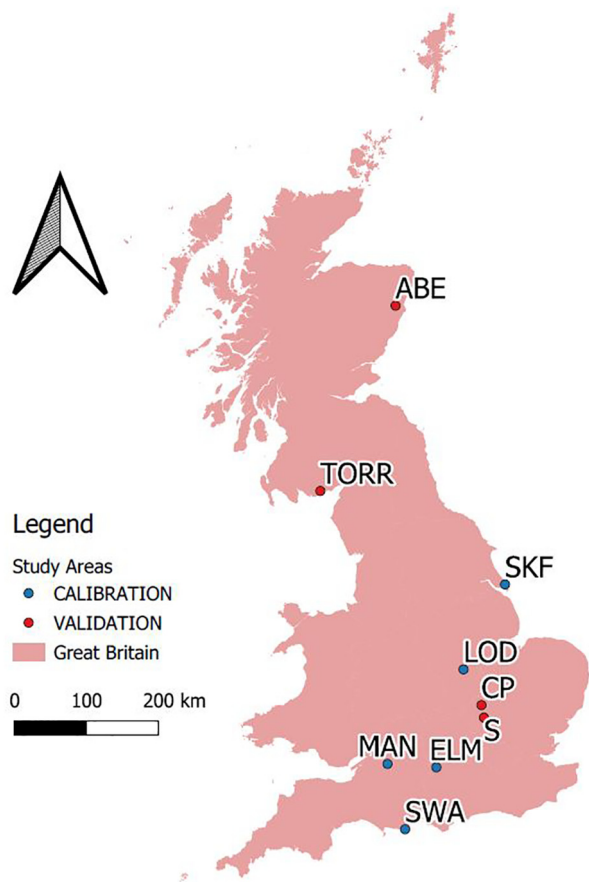
#### 2.2.1. Spatial modelling approach 1

Spatial modelling approach 1 used input vector data in the form of field delineations from the Rural Payments Agency in the UK, land cover (UK Centre for Ecology & Hydrology, 2017), and NATMAP soil associations (Farewell et al., 2011; Hallett, 2010). During the first step, the field parcels were categorised in one of the four land cover groups of the national soil map of England and Wales: arable (AR), improved grassland (IG), woodland and rough grazing (W/RG), and other which included water (OT) (Farewell et al., 2011).

The next step was to identify the soil series that each soil association was made up from and fit splines to the whole soil profile, to derive a value for the organic carbon content (OCC) and bulk densities for the depth of 0–10 cm. In England and Wales, each soil association comprises one or more soil series with an indicative proportion of those series (Table A.2 in Appendix A) each with a specified OCC and bulk density value to a depth of about 150 cm (Fig. A.1 in Appendix A) (Farewell et al., 2011; Hallett, 2010). The original measurements of organic carbon used in the National Soil Resources Institute (NSRI) dataset were made using the Tinsley loss on ignition (LOI) method, (Kalembasa and Jenkinson, 1973) and to standardise the results the LOI values (units: g (100 g soil)<sup>-1</sup>) were converted to an organic carbon content (OCC; unit: g C (100 g soil)<sup>-1</sup>) using Eq. (1) (Ball, 1964) with a correlation coefficient of 0.99 for an LOI range of 5.8 to 88.5 g (100 g soil)<sup>-1</sup>.

$$OCC = 0.476 \times LOI - 1.87 \quad (1)$$

The values of bulk density in the NSRI dataset were measured using the pedogenic Soil Survey and Land Research Centre (SSLRC) method



**Fig. 1.** Measurements of soil organic carbon and bulk density for a calibration dataset (blue dots) were taken on grassland areas near Skeffling (SKF), Loddington Farm (LOD), Manor Farm (MAN), Elm Farm Organic Research Centre (ELM), and a farm near Swanage (SWA). Validation measurements (red dots) were taken at Craibstone near Aberdeen (ABE), Torr Organic Farm (TORR), Clapham Park (CP), and Silsoe (S).

(Avery and Bascomb, 1982). In order to derive a value for the OCC and bulk densities for the same depth as the field measurements of 0–10 cm, we fitted a relationship between OCC (Fig. A.1.a in Appendix A) and bulk density (Fig. A.1.b in Appendix A) with depth for each land cover and soil association. This was done using the R packages *ithir* (Malone, 2019), *agp* (Gramacy, 2016), *dplyr* (Wickham et al., 2021) sp. (Pebesma et al., 2021) and *openxlsx* (Schauberger et al., 2021). Creating these splines, allowed the prediction of the SOC for any specified soil depth with a 1 cm precision depth interval.

The overall OCC and bulk density of each soil association for the specified depth were derived from the weighted mean average of the component soil series using the *propagate* (Spiess, 2018) package in R. The SOC stock (0–10 cm; unit  $t\ ha^{-1}$ ) was then derived using Eq. (2) (Taalab et al., 2013),

$$SOC_i\ stock = BD \times OCC \times d_i \quad (2)$$

where  $SOC_i\ stock$  is the soil organic carbon stock for the depth increment  $i$  ( $t\ C\ ha^{-1}$ ),  $BD$  is the soil bulk density ( $g\ cm^{-3}$ ),  $OCC$  is the organic C content per unit mass of dry soil ( $g\ C\ (100\ g\ soil)^{-1}$ ), and  $d_i$  is the soil thickness of the depth increment  $i$  (cm). Lastly, the SOC for each delineated field was the multiplication product of the per hectare SOC stock with the area of the field shapefile.

The soil associations across the nine locations were primarily clays or loams, and none were characterised by a large gravel or stone content. Hence it was unnecessary to include the gravel content during the

estimation of the SOC stocks. A diagrammatic representation of the steps followed for this approach can be found in more detail at Appendix B, Fig. B1.

### 2.2.2. Spatial modelling approach 2

Spatial modelling approach 2 (Model 2), used Digital Soil Mapping (DSM) to create a  $100\ m \times 100\ m$  raster grid dataset of soil properties in Great Britain, at set depth intervals to a depth of 150 cm, as described by Campbell (2018). The dataset combines the above NSRI data, with representative soil series profiles from the equivalent National Soil Inventory from the Scotland database (Lilly et al., 2010), and data from the National Soil Survey (NSI). The soil properties, which included LOI values and soil and clay contents, were predicted by a combination of the spline method described earlier (for the fixed depth intervals) and then through DSM, by utilising the Boosted Regression Models method using climate, organisms, relief, parent material, and landscape position and environmental covariates (Campbell, 2018).

In order to obtain the soil properties for a depth of 0–10 cm, we used a depth weighted sum of the discrete 0–5 and 5–15 cm depths and aggregated the value for the 0–15 cm depth. We then produced a  $100\ m \times 100\ m$  grid raster, for the depth of 10 cm with the calculated LOI, clay, sand values, model uncertainties and the horizontal  $x$  and  $y$  coordinates for each pixel using the *rgl* (Murdoch and Daniel, 2021), raster (Hijmans et al., 2021) and *sp*. (Pebesma et al., 2021) R libraries. This was followed by the production of three  $100\ m \times 100\ m$  grid point shapefiles that were merged using the QGIS 3.20 (QGIS, 2021) software. For the creation of the grid with the known LOI, clay and sand values, Thiessen polygons from the points were created with an influence area of 1 ha ( $100\ m \times 100\ m$  squares) and were later overlaid to the vector land cover/soil association layer in QGIS. This resulted in every 1 ha square grid being made up of a combination of land covers and soil associations (Fig. 2b).

The *propagate* package in R (Spiess, 2018) was used to calculate the OCC and its uncertainty using Eq. (1). The bulk density of non-arable mineral soils ( $BD_{arable}$ ;  $g\ cm^{-3}$ ) in England was calculated using a pedotransfer function (Hollis et al., 2012; Eqs. (3) & (4)) where OCC is measured in %, and *Sand%* and *Clay%* is measured in terms of % sand and % clay respectively.

$$BD_{mineral} = 0.69794 + (0.750636 \times \text{Exp}(-0.230355\ OCC\%)) + (0.0008687\ Sand\%) - (0.0005164\ Clay\%) \quad (3)$$

In those cases where the land use was arable, a modified equation was used to calculate the bulk density (Eq. (4)).

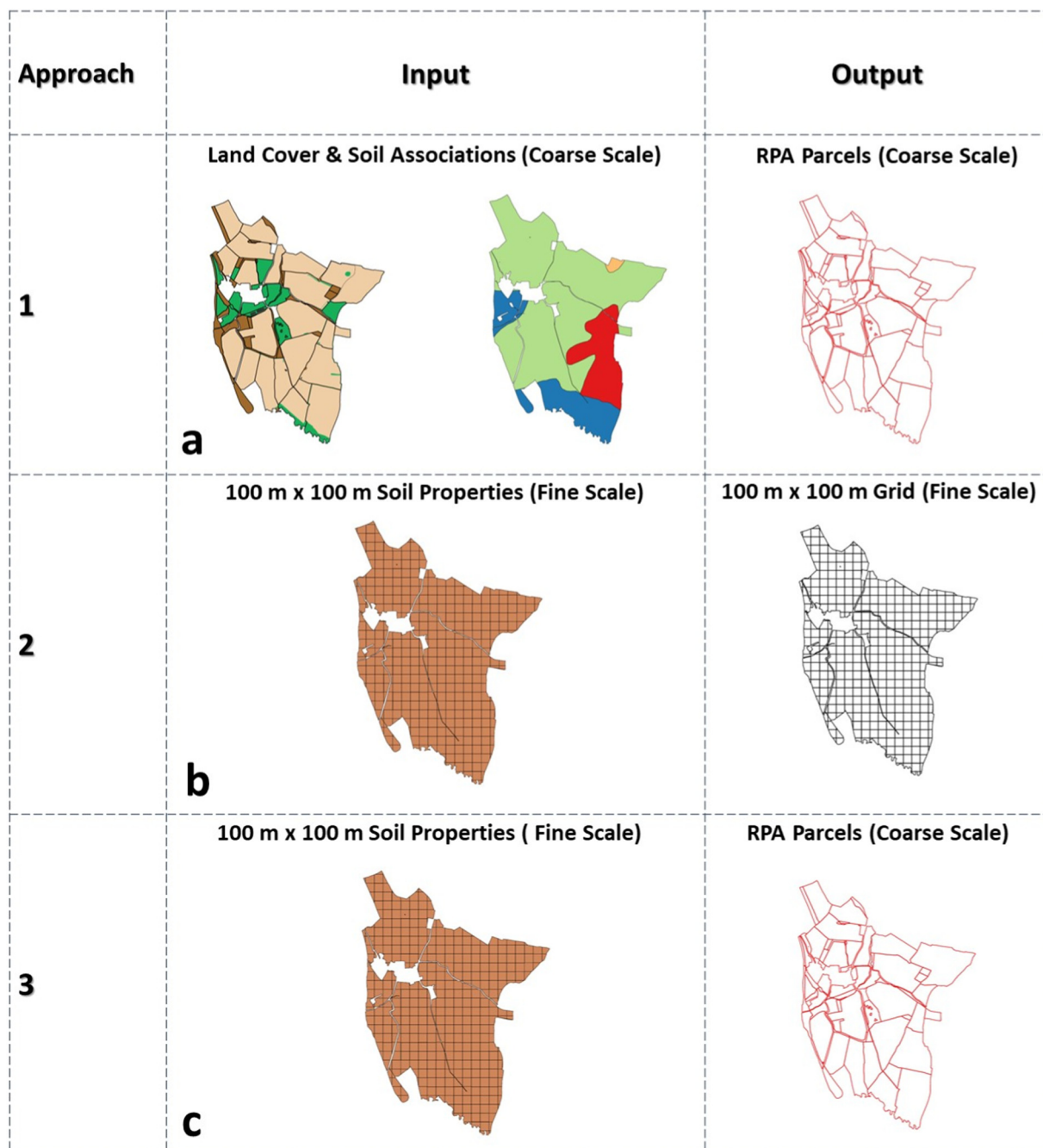
$$BD_{arable} = 0.80806 + (0.823844 \times \text{Exp}(-0.27993\ OCC\%)) + (0.0014065\ Sand\%) - (0.0010299\ Clay\%) \quad (4)$$

Because of different environmental conditions in Scotland, Eq. (5) was used to derive the bulk density of mineral soils ( $BD_{minScot}$ ). The equation included the horizon thickness ( $Hor_{thick}$ ; cm), the natural logarithm ( $\log$ ) of the OCC measured in  $g\ C\ (100\ g\ soil)^{-1}$  and the logarithm of the odds ratio ( $\text{logit}$ ) of the Clay ( $g\ clay\ (100\ g\ soil)^{-1}$ ) as inputs (Gagkas and Lilly, personal communication 2021).

$$BD_{minScot} = 1.29101 - (0.33984 \times \log\ OCC) + (0.05622 \times \text{logit}(Clay)) + 0.01259 \times Hor_{thick} \quad (5)$$

$$\text{Logit} = \log\ ((Clay)/(100 - Clay)) \quad (6)$$

The *propagate* package in R (Spiess, 2018) was used to calculate the bulk density and the uncertainty of each  $100\ m$  square grid by using first/second-order Taylor expansion including the covariates. To allow comparison with Model 1, a SOC stock value was derived for each land cover and soil association combination using the land cover and soil association layer in QGIS (Fig. 2b). These SOC stock values were distributed according to the area of each combination within the square grid. This method allowed an



**Fig. 2.** Farm scale spatial modelling approaches (Models) of soil organic carbon (SOC) stocks with the datasets used to develop them illustrated for the study site at Loddington: a) Spatial modelling approach 1 (Model 1) using land cover and coarse-scale soil association designations, and coarse-scale land parcel boundary data derived from the Rural Payments Agency (RPA), b) Spatial modelling approach 2 (Model 2) using fine-scale 100 m × 100 m soil properties data with predicted values of loss on ignition (LOI), clay and sand content, and fine-scale 100 m × 100 m grid squares data, and c) Spatial modelling approach 3 (Model 3) using input data from a 100 m × 100 m square grid with predicted values of loss on ignition (LOI), clay and sand content, and outputs using coarse-scale Rural Payments Agency (RPA) land parcel boundary data.

estimation of the uncertainty of the stocks by propagating it in all four cardinal directions and to a soil depth of 10 cm. A diagrammatic representation of the steps followed for this approach can be found in more detail at Appendix B, Fig. B2.

### 2.2.3. Spatial modelling approach 3

Spatial modelling approach 3 (Model 3) used the same soil properties described for the 100 m square grid raster in Model 2. However, whereas Model 2 delineated areas using the 100 m grids, Model 3 delineated the farm into fields that contained one or more areas of a combination of a

land cover and soil association (Fig. 2c). This resulted in each field parcel having an LOI, clay and sand value that was calculated as the mean of all the 100 m × 100 m grid squares that fell inside the field boundaries. We then used the same calculation steps (e.g. Eqs. (3)–(6)) as in Model 2 to obtain the OCC and the bulk density datasets. The calculation of the SOC for the area of each land cover/soil association combination, for the 0–10 cm depth, was again performed by using Eq. (2). Here, the uncertainty associated with the area (ha) was that of the UKCEH land cover classification, as the soil associations dataset was assumed unbiased, and not having any uncertainty related to its landscape (x, y) placement. Similar to Model 2, this

**Table 1**

Analytical representation of the calibration and validation performance results of the three spatial modelling approaches (models) of soil organic content (SOC). The regression equations describe the relationship between the estimated ( $SOC_{pred}$ ;  $t\ ha^{-1}$ ) and measured ( $SOC_{meas}$ ;  $t\ ha^{-1}$ ) soil organic carbon values to the depth of 10 cm. The number of observations (n),  $R^2$ , root mean square error (RMSE), and upper and lower confidence limits of the intercept and the slope, and the range of measured and estimated values are also presented.

Model	Regression equation	n	$R^2$	RMSE	Intercept confidence limits (95%)	Slope confidence limits (95%)	SOC range ( $t\ ha^{-1}$ )	
							Estimated	Measured
<b>Calibration</b>								
1	$SOC_{pred} = 0.293\ SOC_{meas} + 28.2$	19	0.39	16.0	18.2–38.1	0.1–0.5	29.0–51.6	28.1–89.7
2	$SOC_{pred} = 0.403\ SOC_{meas} + 18.9$	90	0.50	15.8	14.8–23.0	0.3–0.5	20.0–78.3	20.3–97.7
3	$SOC_{pred} = 0.436\ SOC_{meas} + 15.6$	19	0.64	17.2	6.8–24.5	0.3–0.6	26.1–57.1	28.1–89.7
<b>Validation</b>								
1	$SOC_{pred} = 0.048\ SOC_{meas} + 37.0$	13	0.43	18.3	35.0–39.1	0.0–0.1	38.5–40.4	39.7–74.8
2	$SOC_{pred} = 0.668\ SOC_{meas} + 12.9$	54	0.68	11.0	5.5–20.2	0.5–0.8	31.6–84.1	25.9–93.6
3	$SOC_{pred} = 0.744\ SOC_{meas} + 8.83$	13	0.69	8.3	–9.6–27.3	0.4–1.1	36.0–69.8	39.7–74.8

last method was used to estimate the uncertainty of the stocks by propagating it across the four cardinal directions and to a depth of 10 cm. A diagrammatic representation of the steps followed for this approach can be found in more detail at Appendix B, Fig. B3.

**2.3. Comparison of spatial model outputs with measurements**

The measurements from Skeffling (SKF), Loddington Farm (LOD), Manor Farm (MAN), Elm Farm Organic Research Centre (ELM), and the farm near Swanage (SWA) previously described, were used as calibration datasets (Fig. 1). The measurements from Craibstone near Aberdeen (ABE), Torr Organic Farm (TORR), Clapham Park (CP), and Silsoe (S) were used as validation datasets (Fig. 1).

Additionally, the measurements of three fields present in the Loddington Farm (LOD), (Fig. 5) were used to look at how well the spatial modelling approaches were behaving when deployed in a specific farm and the level of in-farm stored SOC variation that they could pick up.

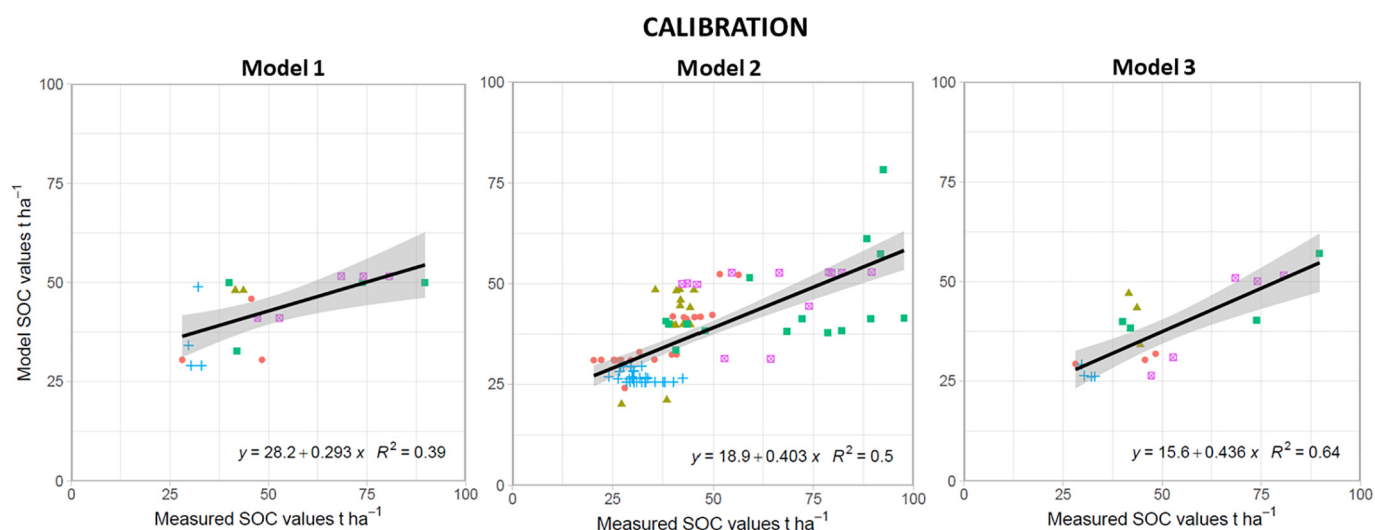
For Models 1 and 3, where the outputs were expressed at a field scale, we assumed that the SOC stock was constant within each land parcel. For the calibration and validation datasets, we performed a linear regression of the estimated values against the calculated mean of the measured SOC of the sampled points within each land parcel of interest. For the fine management scale Model 2, we assumed that the SOC stock was constant within

the boundaries of each 100 m square grid. For the calibration and validation of all three models, the  $R^2$  and RMSE values were calculated and used to compare the spatial modelling approaches.

**2.4. Spatial accounting approach of carbon stocks**

Voluntary certified carbon sequestration schemes are typically concerned with i) the additionality of the change i.e. the change has only occurred as a result of the certification process, and ii) the permanence of change e.g. can the change be maintained for the next 100 years? (Grem and Aklilu, 2016; Badgery et al., 2020). Within the UK Land Carbon Registry, there are two types of units: i) pending issuance units (PIUs) which describes an anticipated carbon sequestration over 5–10 year periods in the future, and ii) full carbon credits which are verified accumulations of carbon storage (Woodland Carbon Code, 2022). For the three spatial methods, we compared the assumed SOC, and the value of the additional carbon stored assuming i) the level of soil carbon is increased by  $10\ t\ C\ ha^{-1}$  over the measured value, and ii) the same level of carbon compared with a baseline derived from the models.

To illustrate the financial and economic implications of the approaches, we selected an indicative value of carbon of  $\pounds 100\ (t\ C)^{-1}$ , which lies within a wide range of values reported in the literature. Graves et al. (2015) estimated the value of soil carbon in terms of positive effects on crop yields,



**Fig. 3.** Calibration dataset: relationship between estimated and measured soil organic carbon (SOC) values (0–10 cm) using spatial modelling approaches 1 (Model 1), 2 (Model 2) and 3 (Model 3) across five calibration sites: ● Elm Farm (ELM), ◆ Loddington (LOD), ■ Manor Farm (Man), + Skeffling (SKF), and Swanage (SWA)

✖

soil water storage, and soil conservation, and assumed a value of £51 ( $\text{t CO}_2\text{e}^{-1}$ ), equivalent to £187 ( $\text{t C}^{-1}$ ) for the effect of carbon sequestration on climate change. The UK Government has provided guidance on the social value of soil carbon in reducing atmospheric  $\text{CO}_2$  for policy analysis (Department of Energy and Climate Change, 2009). For 2000, Stern (2007; page 323) quoted a social value of carbon (2000 prices) of £100  $\text{t C}^{-1}$ , and the current mid-range estimate for policy appraisal in the UK using 2022 prices is about £250 ( $\text{t CO}_2\text{e}^{-1}$ ), equivalent to £916 ( $\text{t C}^{-1}$ ) (UK Government, 2021b). In December 2021, the mean quoted price on the UK Emissions Trading Scheme and the EU Emissions Trading Scheme, covering the power generation sector, was £68–74 ( $\text{t CO}_2\text{e}^{-1}$ ), equivalent to £250–270 ( $\text{t C}^{-1}$ ) (EMBER, 2021). The UK Department for Business Energy and Industrial Strategy (2019) reported a marginal abatement cost of reducing atmospheric  $\text{CO}_2$  levels with a mean value of £70  $\text{t C}^{-1}$  for 2021 within a range of £35–105  $\text{t C}^{-1}$ . The price currently received in the UK for verified woodland carbon ranges from £17 to £24 ( $\text{t CO}_2\text{e}^{-1}$ ), equivalent to £62 to £88 ( $\text{t C}^{-1}$ ) (Woodland Carbon Code, 2022).

### 3. Results

#### 3.1. Calibration sites

Across the five calibration sites, there was a positive relationship between the measured and estimated soil organic carbon values to a depth of 10 cm for all three spatial modelling approaches (Table 1). The lowest correlation ( $R^2 = 0.39$ ) was obtained from the coarse input; coarse output Model 1 which had a root mean square error (RMSE) of  $16.0 \text{ t ha}^{-1}$ . Model 2, with the combination of fine input data and fine output data, had a higher correlation ( $R^2 = 0.50$ ) with an RMSE of  $15.8 \text{ t ha}^{-1}$ . The highest coefficient of determination ( $R^2 = 0.64$ ) was obtained using Model 3, comparing fine input data with coarse outputs, with an RMSE of  $17.2 \text{ t ha}^{-1}$ . The 95% confidence interval of the regression equation is illustrated by the grey shaded area in Fig. 3.

The slope of the regression equation for Model 1 was 0.293, compared to 0.403 for Model 2 and 0.436 for Model 3, indicating that in each case the observed variation in the estimated soil carbon contents was less than the measured values. For example, for Model 1 ( $n = 19$ ), while the averages of the measured values within each sampled field parcel ranged from 28 to  $90 \text{ t C ha}^{-1}$ , the estimated values only ranged from 29 to  $52 \text{ t C ha}^{-1}$ . For Model 2, the larger number of samples ( $n = 90$ ) increased the measured range (20 to  $98 \text{ t C ha}^{-1}$ ), but this was still larger than the range of estimated values (20 to  $78 \text{ t C ha}^{-1}$ ). For Model 3 ( $n = 19$ ), the estimated values ranged

**Table 2**

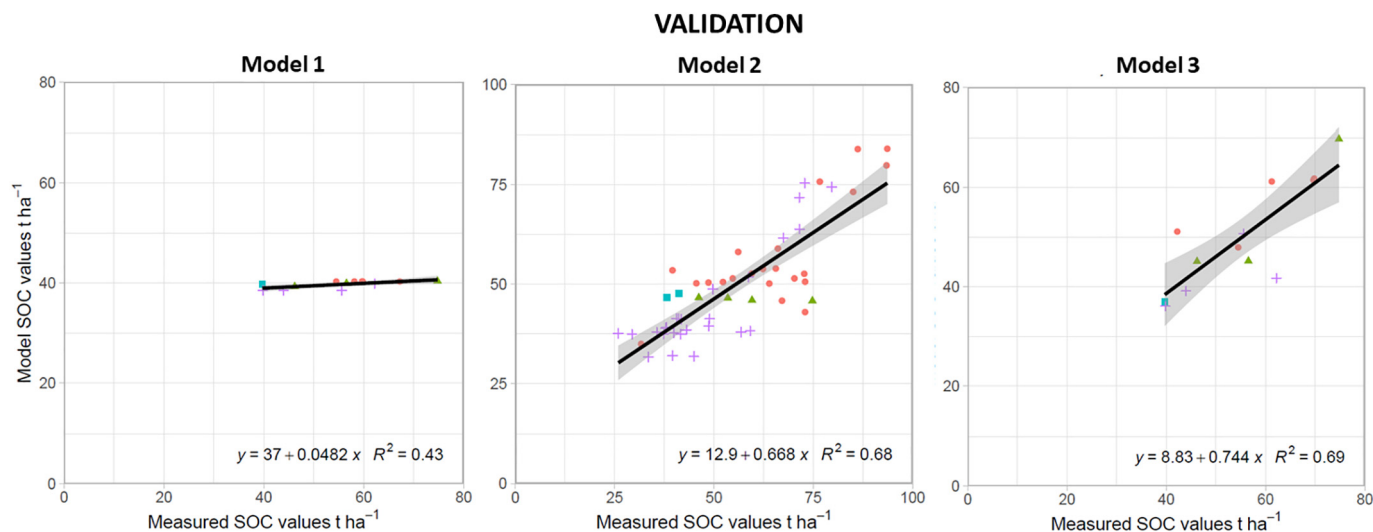
Weighted mean measured and estimated soil organic content (SOC) (0–10 cm) and its value of sampled fields using the three spatial modelling approaches (Models). Fields are ranked according to measured values using Model 2.

Farm/site	Weighted mean SOC content value of sampled fields ( $\text{t ha}^{-1}$ )					
	Model 1		Model 2		Model 3	
	Measured	Model	Measured	Model	Measured	Model
Skeffing (SKF)	31.6	35.7	31.6	26.8	31.6	26.7
Elm Farm (ELM)	35.4	33.9	35.9	31.6	35.4	29.9
Silsoe (S)	39.7	39.8	39.7	37.6	39.7	36.9
Loddington (LOD)	43.0	48.0	40.5	40.4	43.0	39.5
Torr Organic (TORR)	41.2	39.2	48.3	44.8	41.2	41.1
Clapham (CP)	56.5	39.8	58.5	52.7	56.5	50.2
Manor Farm (MAN)	67.5	48.0	61.4	45.7	67.5	44.0
Swanage (SWA)	65.5	48.2	64.5	47.8	65.5	43.5
Aberdeen (ABE)	59.5	40.3	65.3	59.2	59.5	58.9
Mean	48.9	41.4	49.5	42.9	48.9	41.2

from 26 to  $57 \text{ t ha}^{-1}$  while the average measured values within each sampled field parcel ranged from 28 to  $90 \text{ t ha}^{-1}$ .

#### 3.2. Validation sites

The validation dataset also showed a positive correlation between the estimated and the measured soil organic carbon contents (Table 1 and Fig. 4). The poorest correlation ( $R^2 = 0.43$ ) was again obtained using Model 1, while Models 2 and 3 with the fine input data had  $R^2$  values of 0.68 and 0.69 respectively. The RMSE ranged from  $18.3 \text{ t ha}^{-1}$  for Model 1, to 11.0 and  $8.3 \text{ t ha}^{-1}$  for Model 2 and 3 respectively. The value of the slope ranged from 0.048 for Model 1 to 0.668 for model 2 and 0.744 for Model 3. Hence the range of the estimated values was again less than the measured values. For Model 1 ( $n = 13$ ) the estimated values ranged from 38 to  $40 \text{ t ha}^{-1}$ , while the mean measured values in each field parcel ranged from 40 to  $75 \text{ t ha}^{-1}$ . For Model 2 ( $n = 54$ ), the estimated values ranged from 32 to  $84 \text{ t ha}^{-1}$  broadly similar to the range of measured values from 26 to  $94 \text{ t ha}^{-1}$ . For Model 3 ( $n = 13$ ), the predicted values ranged from 36 to  $70 \text{ t ha}^{-1}$  similar to a range of measured values from 40 to  $75 \text{ t C ha}^{-1}$ . Overall, each of the models predicted lower levels of SOC stocks than the measured levels. The mean reduction was 19% with Model 1, 15% for Model 2, and 14% for Model 3.



**Fig. 4.** Validation dataset: relationship between estimated and measured soil organic carbon (SOC) values (0–10 cm) using spatial modelling approaches 1 (Model 1), 2 (Model 2) and 3 (Model 3), across four validation sites: ● Aberdeen (ABE), ◆ Clapham Park (CP), ■ Silsoe (S), and + Torr Organic Farm (TOR).

### 3.3. Quantity and value of carbon stock across farms

The next step of the analysis was to determine how the three modelling approaches interact with the choice of accounting method. Using 100 m × 100 m grids as an output (Model 2), the lowest mean measured SOC (0–10 cm) of 31.6 t ha<sup>-1</sup> was at Skeffing, with the highest measured SOC value of 65.3 t ha<sup>-1</sup> at Aberdeen. The mean measured SOC (0–10 cm) at a field scale (as used in Models 1 and 3) ranged from 31.6 t ha<sup>-1</sup> at Skeffing to 59.5–67.5 t ha<sup>-1</sup> at Aberdeen, Swanage and Manor Farm (Table 3).

As previously indicated, the estimated values of SOC were less than the measured values, with a tendency of the spatial modelling approaches to underestimate the value of SOC at sites with high soil organic carbon. Hence Model 2 predicted a SOC (0–10 cm) of 59.2 t ha<sup>-1</sup> at Aberdeen, compared to a measured value of 65.3 t ha<sup>-1</sup>. Model 1 predicted a SOC (0–10 cm) of 40.3 t ha<sup>-1</sup> at Aberdeen, compared to a measured value of 59.5 t ha<sup>-1</sup>, and Model 3 predicted a SOC of 58.9 t ha<sup>-1</sup> at Aberdeen compared to a measurement of 59.5 t ha<sup>-1</sup> (Table 2).

Two approaches were analysed to determine the potential receipts of carbon payments that could be received by the farms. The first assumed that the level of soil carbon is increased by 10 t C ha<sup>-1</sup> over the measured value, and the second approach assumed the same final level of carbon but compared to the modelled values as a baseline. In approach 1, assuming a measured increase in SOC of 10 t C ha<sup>-1</sup> and a carbon value of £100 (t C)<sup>-1</sup>, would have resulted in a carbon value benefit of £1000 ha<sup>-1</sup> on each farm and with each method. The new SOC content to achieve this varied between farms, but the values from the three spatial approaches for a given farm were broadly similar (Table 3). Using approach 2 resulted in noticeable differences between farms and spatial modelling methods. Using Model 2 as the initial baseline, the calculated mean increase in SOC was worth £1657 ha<sup>-1</sup>, ranging from £1010 ha<sup>-1</sup> at Loddington to £2570–2670 ha<sup>-1</sup> at Manor Farm, and Swanage (Table 3). Using Model 1, the mean derived value was marginally higher than with Model 2, and the calculated value of the assumed increased in carbon ranged from £500 ha<sup>-1</sup> at Loddington to £2670–2950 ha<sup>-1</sup> at Clapham, Swanage, Aberdeen and Manor Farm (Table 3). The mean value of the increase (£1760 ha<sup>-1</sup>) based on Model 3 was similar to Model 1 (£1750 ha<sup>-1</sup>), but the value was more consistent across seven of the sites ranging from £1010–1630 ha<sup>-1</sup>, but it reached £3200–3350 ha<sup>-1</sup> at Manor Farm and Swanage.

### 3.4. Application at a farm-scale

The estimated SOC stock (0–10 cm) in t ha<sup>-1</sup> determined by each spatial modelling approach for each field at Loddington is shown in Fig. 5. These values were used to determine the stored SOC (0–10 cm) for the 317 ha at Loddington. The estimate was 12,356 t using Model 1, 13,815 t using Model 2, and 13,472 t using Model 3. The use of coarse data inputs with Model 1 resulted in less within-farm variation than the two spatial modelling approaches using input data at a finer spatial resolution.

From the three measured parcels, land parcel B comprised two soil associations, returned the highest mean SOC values and stocks in all three models, and land parcel C the lowest. As can be observed in Table A3 in Appendix A, the spatial modelling approach with the combination of coarse input data and coarse management scale (Model 1), gave similar SOC values to all land parcels with the same land cover/soil association combination. By contrast, the use of fine-scale input data enabled the identification of within field and between field variations.

## 4. Discussion

This discussion starts by examining the benefits of using fine resolution inputs to develop farm-level inventories of SOC. It then examines sources of error and uncertainty, the benefits of the final predictions being provided at a field or 100 m grid-square scale, and the implications of spatial modelling approach use on carbon sequestration payments.

### 4.1. Benefits of fine resolution input data for farm-scale inventories

In the context of national targets for net-zero GHG emissions, there is a need to develop robust farm-scale SOC inventories of soil carbon storage. Ideally, it would be best to have standardised measured values of soil carbon and bulk density for each field on specified dates to specified depths, but such data are costly in terms of time and resources. A potential cost-effective alternative is to use validated approaches that can predict SOC levels, with a stated level of uncertainty, moderated by spatial inputs which can be derived more easily. For both calibration and validation datasets, using a 100 m × 100 m input dataset (Campbell, 2018) increased the proportion of the variation in SOC that could be explained to 50–69% (Models 2 and 3), compared to 39–43% with the coarser NATMAP dataset (Model 1). Across the calibration and validation dataset, the RMSE associated with Model 2 (11.0–15.8 t SOC ha<sup>-1</sup>) and Model 3 (8.3–17.2 t SOC ha<sup>-1</sup>) tended to be less than with coarse-scale Model 1 (16.0–18.3 t SOC ha<sup>-1</sup>).

In addition to explaining a higher proportion of the variation, the slopes of the regression equation of the estimated to measured stocks using Model 2 (0.40–0.67) and 3 (0.44–0.74) were substantially greater than that using Model 1 (0.05–0.29). This increased slope means that Models 2 and 3 were better able to differentiate between areas of low and high soil carbon, which has important implications for carbon payments. For example, as demonstrated for Loddington, Models 2 and 3 were able to pick up field-to-field and in-field variation not captured by Model 1. Hence it seems that the finer resolution models can enable more informed management of soil carbon.

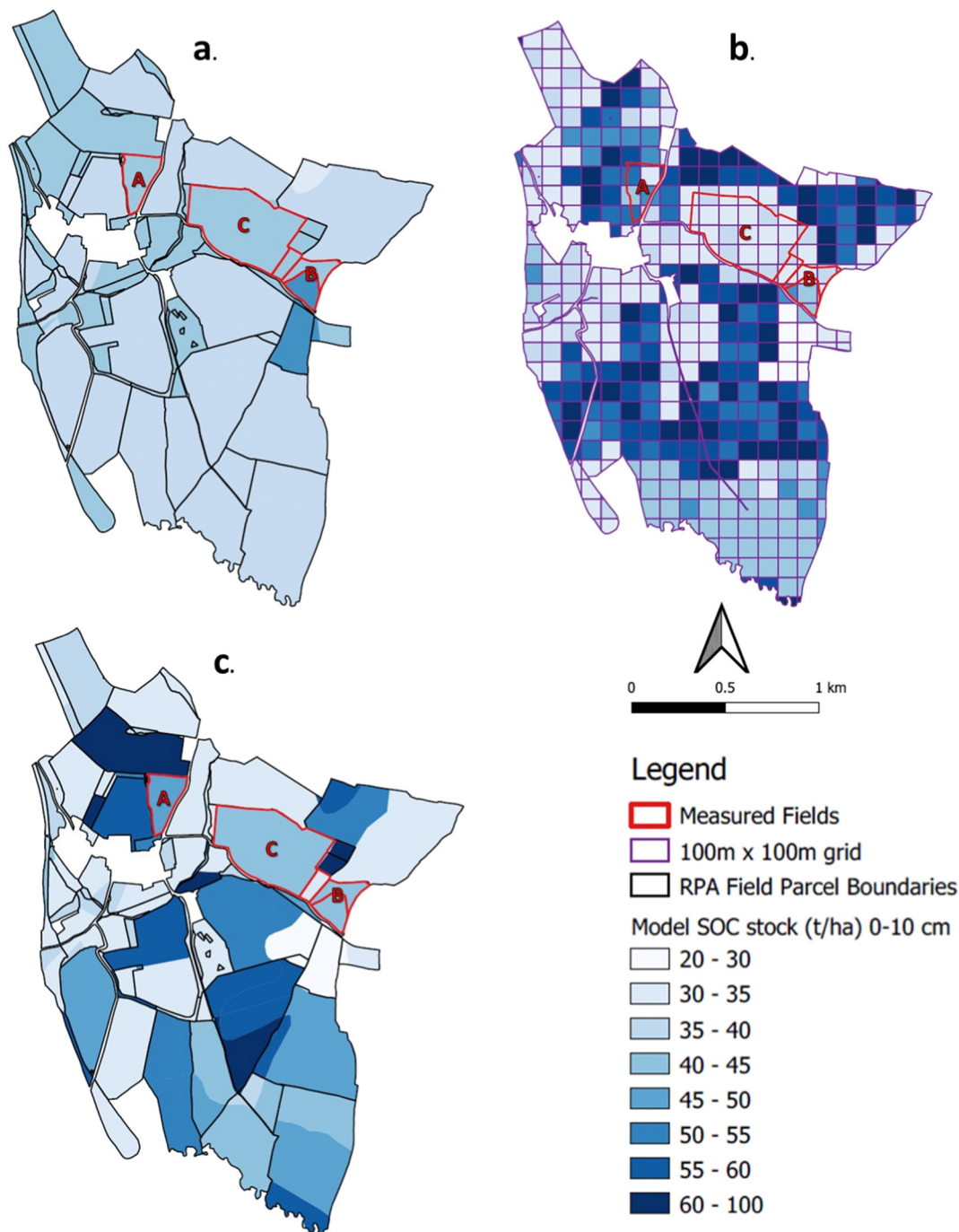
One reason why Models 2 and 3 were able to estimate a higher proportion of variation than Model 1 is that the soil properties dataset developed by Campbell (2018) considered the local variation of soil formation characteristics such as altitude, climate, relief, parent material, and time (Jenny, 1941). In addition, the Campbell dataset accounted for spatial variation

**Table 3**

Assumed new SOC, based on measured values and assuming an increase in SOC of 10 t ha<sup>-1</sup>, and the value<sup>a</sup> of the change to new SOC starting from the modelled baseline.

Farm/site	Model 1		Model 2		Model 3	
	Assumed new SOC (t ha <sup>-1</sup> )	Value above modelled baseline (£ha <sup>-1</sup> )	Assumed new SOC (t ha <sup>-1</sup> )	Value above modelled baseline (£ha <sup>-1</sup> )	Assumed new SOC (t ha <sup>-1</sup> )	Value above modelled baseline (£ha <sup>-1</sup> )
Skeffing (SKF)	41.6	590	41.6	1480	41.6	1490
Elm Farm (ELM)	45.4	1150	45.9	1430	45.4	1550
Silsoe (S)	49.7	990	49.7	1210	49.7	1280
Loddington (LOD)	53.0	500	50.5	1010	53.0	1350
Torr Organic (TORR)	51.2	1200	58.3	1350	51.2	1010
Clapham (CP)	66.5	2670	68.5	1580	66.5	1630
Manor Farm (MAN)	77.5	2950	71.4	2570	77.5	3350
Swanage (SWA)	75.5	2730	74.5	2670	75.5	3200
Aberdeen (ABE)	69.5	2920	75.3	1610	69.5	1060
Mean	58.9	1750	59.5	1657	58.9	1760

<sup>a</sup> Carbon value was assumed to be 100 £ (t C)<sup>-1</sup>.



**Fig. 5.** Predicted soil organic carbon (SOC) stock ( $\text{t ha}^{-1}$ ) (0–10 cm) for a) each field parcel and highlighted measured parcels (in red) in the Loddington farm using spatial modelling approach 1 (Model 1), b) each  $100 \text{ m} \times 100 \text{ m}$  square grid using spatial modelling approach 2 (Model 2), and c) each field parcel using spatial modelling approach 3 (Model 3). The SOC stock values are shown using a  $5 \text{ t ha}^{-1}$  increment for values between 30 and  $60 \text{ t ha}^{-1}$  and greater increments at the extremes.

in bulk density, OCC and the soil associations, both across the landscape ( $x, y$ ) and with depth ( $z$ ). It is particularly important to account for variations in bulk density when determining values of SOC from OCC measurements (Taalab et al., 2013).

Although Model 2 and 3 were able to explain a higher proportion of the variation in SOC than Model 1, overall, both spatial modelling approaches still predicted lower variation than the measured SOC values. This is demonstrated by the slope values of less than 1, and large intercepts for the regression line of  $28.2\text{--}37.0 \text{ t SOC ha}^{-1}$  for Model 1,  $12.9\text{--}18.9 \text{ t SOC ha}^{-1}$  for Model 2, and  $8.8\text{--}15.9 \text{ t SOC ha}^{-1}$  for Model 3. This means that although the finer resolution dataset was better able to account for SOC

differences, Models 2 and 3 still tended to underestimate the SOC value of soils high in soil carbon. The tendency for spatial models to underestimate areas of high soil carbon has previously been noted by Gregory et al. (2014).

Potential sources of error and uncertainty when comparing estimated predictions with measured results can arise from three sources. Firstly, regarding the measured data, the SOC and bulk density measurements are within typical analytical mean probable errors (2.7–5.8%) (Schrumpp et al., 2011) and the methods and location of the measurements were also clearly recorded. Secondly, in terms of the input data, the soil association dataset used in Model 1 assumes definite borders making the predicted



SOC step changes abrupt, while they are typically gradual. The 100 m × 100 m dataset (Campbell, 2018), used in Model 2 and 3 assumed land covers as they existed in 2000 (LCM 2000), whereas the measured values were obtained between 2013 and 2016. However, to our knowledge, all of the grassland sites were grassland in both 2000 and 2013–2016. In addition, the spatial modelling approaches do not address the temporal aspects of SOC decline or increase resulting from a land cover change. To account for such effects would require additional data on the timing of land cover changes. Lastly, the third source of error relates to the algorithms used in the modelling approaches. The data used to create the spatial modelling approaches with the fine-scale input data (Models 2 and 3), performed much better in predicting the texture properties (clay and sand) than the LOI with RMSE values equal to  $\pm 9.1$  g clay (100 g soil)<sup>-1</sup> and  $\pm 15.6$  g clay (100 g soil)<sup>-1</sup> respectively (Campbell, 2018). Similarly, the equations used for the calculation of these models' parameters had a correlation coefficient of 0.99 for the LOI/OCC calculation (Ball, 1964) and an R<sup>2</sup> ranging from 0.40 to 0.68, for the bulk density depending on the type and the characteristics of soil (Hollis et al., 2012).

#### 4.2. Benefits and costs of different carbon baseline estimates

On a traditional farm where decisions are taken at a field level, farmers might be more interested in estimates of SOC for individual fields (e.g., Model 3) rather than each 100 m × 100 m square grid (Model 2). However, by using a model with the combination of fine-scale input data and fine management scale, like Model 2, a farmer can pick up the in-field variations and be able to adjust their management practices according to factors like the topography and the soil type of that location. The mean measured field sizes of the nine study areas ranged from 3.74 ha for the farm in Swanage to 12.39 ha for the Torr Organic Farm.

#### 4.3. Implications of spatial modelling approach choice on financial payments

Carbon farming can potentially provide an income to farmers and landowners who can sell the credits they earn in carbon markets where large scale GHG emitters can purchase them to offset their own emissions. One major challenge is that soils depending on their texture, depth and mineral content absorb different amounts of carbon (Choudhury et al., 2016; Jobbágy and Jackson, 2000; Yu et al., 2020). While certain practices such as no-till and cover cropping (Hillier et al., 2011; Jian et al., 2020; Zhang et al., 2006) can increase carbon storage, quantifying the stored amount is crucial in order to assign the value of the change.

Although soil carbon markets are not yet fully developed, one example includes the Emissions Reduction Fund in Australia (Australian Government Department of Industry, Science, Energy and Resources, 2021). In the UK, there are plans for the Sustainable Farming Incentive to pay farmers and landowners for an increase in SOC stocks (Department for Environment Food & Rural Affairs, 2021), and the Environmental Agency is funding a consortium to develop a soil carbon code that will provide farmers with an additional income (Sustainable Soils Alliance, 2021). In the US, the Senate passed the Growing Climate Solutions Act of 2021 (US Government, 2021) and voluntary companies such as IndigoAg and Nori have already enabled farmers to receive carbon credit payments (Farmers Weekly, 2021). However, as Paustian et al. (2019) highlighted there are still no global standards for measuring, verifying or reporting SOC credits in agricultural lands.

In the few existing farm-scale soil carbon modelling studies, predictions are typically limited to averages over the whole farm area (Vandenbygaert et al., 2004). In some cases, the coefficients of correlation (*r*) and determination (R<sup>2</sup>) are reported between the measured and predicted values, but there is no information about the level of precision (Adewale et al., 2019; Correndo et al., 2021; Mikhailova et al., 2016), even though model uncertainty can be derived by propagating the uncertainty of input values. Moreover, rigorous approaches validated against measured values are needed in order to avoid someone claiming carbon credits that do not occur in practice. A possible method is to develop approaches to spatially predict and

evaluate SOC that is appealing to farmers and landowners, who can both be paid for maintaining or increasing soil carbon, while also benefiting from improved soil health and increased crop yields.

In this paper, we assumed a carbon value of £100 (t C)<sup>-1</sup>, which is equivalent to £27 (t CO<sub>2</sub>e)<sup>-1</sup>. This is marginally higher than prices (£17 and £24 (t CO<sub>2</sub>e)<sup>-1</sup>) received for verified woodland carbon sequestration in the UK (Woodland Carbon Code, 2022), but less than the traded price for carbon in the electricity generation sector (£74 (t CO<sub>2</sub>e)<sup>-1</sup>), and about 11% of the social cost of carbon (SCC) (£250 (t CO<sub>2</sub>)<sup>-1</sup>) used in policy analysis. At present, the prices received for reducing GHG emissions through tree and soil management are less than the penalties for emissions in electricity generation, but over time these values should converge. Similarly, if carbon emissions are viewed from a societal perspective, the value of traded carbon sequestration or cost of carbon emissions should converge to the social costs of carbon.

The choice of whether to measure or model the baseline SOC from which to derive a value of an increase in the SOC by 10 t C ha<sup>-1</sup> above the initial measured value could have different financial between farms, and the effect also varied with choice of model. Underestimation of high SOC values, using the spatial modelling approaches, described in Section 4.1 has important financial implications. Using Model 2, because the mean modelled SOC (42.9 t ha<sup>-1</sup>) was less than the mean measured value (49.5 t ha<sup>-1</sup>), an increase to a new measured value of 59.5 t ha<sup>-1</sup> assuming the initial modelled values would result in a mean payment of £1657 ha<sup>-1</sup>, i.e., 66% higher than if the results were only based on measurements. Because Model 2 tended to show a greater underestimation of the measured SOC at high SOC sites, using the model as a baseline meant that the derived carbon benefit was a mean of £1296 ha<sup>-1</sup> for the five sites with low SOC compared to a mean of £2108 ha<sup>-1</sup> for the four sites with the highest SOC. Hence in this example, using the model as a baseline favoured sites that already had a high SOC.

Using both coarse level inputs and outputs with Model 1 resulted in a lower mean estimate of SOC of 41.4 t ha<sup>-1</sup> compared to 42.9 t ha<sup>-1</sup> with Model 2. Hence assuming final measured values of SOC (that were 10 t ha<sup>-1</sup> above the original measured value), and baseline values based on Model 1 would result in an assumed mean increase worth £1750 ha<sup>-1</sup>, 75% higher than the actual increase worth £1000 ha<sup>-1</sup>. Again, because Model 1 underestimated the initial SOC of sites with high SOC values, assuming a modelled baseline benefited the four farms with the highest SOC (range: £2670–2950 ha<sup>-1</sup>) than the five farms with the lowest SOC (range: £500–1200 ha<sup>-1</sup>).

The mean values of measured and modelled SOC using Model 3 were similar to Model 1 (Table 2), and hence the mean benefit to the farmers of the explained increase in carbon, based on Model 3 baseline of £1760 ha<sup>-1</sup>, was 76% higher than the increase if based on measurements. However, because Model 3 was better able that Model 1 to predict the high SOC of some high SOC sites, for seven of the nine sites, the calculated increase in value ranged from £1010 ha<sup>-1</sup> to £1630 ha<sup>-1</sup>. However, by contrast, Model 3 substantially underestimated the initial SOC at Manor Farm and Swanage (by between 22.0 and 23.5 t (C ha<sup>-1</sup>)), where the assumed increase in SOC was worth £3200–3350 ha<sup>-1</sup>.

Overall, the use of models rather than measurements to determine an initial baseline for increases in soil carbon benefitted farmers, but such an approach would be more costly than expected for purchasers of carbon credits. In this example, a coefficient of 0.57–0.62 would need to be applied to mean calculated increases, so that the calculated increases matched the actual increase of 10 t C ha<sup>-1</sup>. The appropriate coefficient will vary depending on the increase in SOC.

#### 4.4. Limitations of the developed spatial modelling approaches and how to overcome them

Each of the examined spatial modelling approaches have potential limitations, and there are errors and uncertainty with the measured data and the inputs and the algorithms in the approaches. International soil carbon accounting approaches such as used by the IPCC (2019) focus on a soil

depth of 0–30 cm. However, in this study, the three spatial modelling approaches were only applied to a depth of 0–10 cm as this was the only spatially explicit available measured dataset. Acquisition of complete measured SOC data to greater depths is hard to come across due to the labour intensity and expenses that are required. The methodology can be applied at deeper depths, if complete spatially explicit datasets to greater depths become available. Further research is recommended to compare the spatial modelling approaches with measured soil carbon values to a depth of at least 30 cm and across a wider range of land covers.

Models 2 and 3 were based on a soil database established for land cover at a specific date. However land cover on farms is not static, and even if the land cover remains the same, management practices can modify the SOC (Badgery et al., 2020; Hamburg et al., 2019; Kirk and Bellamy, 2010; Upton et al., 2016). Hence it is likely that physical measurements will be needed to validate current levels of SOC. However there is an argument that having modelled SOC values calculated for a specific date can be useful in establishing a common baseline from which to predict subsequent change. In order for this to be useful, it will be important to understand the uncertainty associated with such SOC values and the associated financial valuations. One way is to address the financial uncertainty associated with modelled values would be to apply a discounting coefficient. Although this will reduce the financial value of estimated change, it may still be more cost-effective for the farmer than incurring additional costs to derive a more accurate value through other methods.

The three spatial modelling approaches developed in this study take a screenshot of a farm or site at a specific point in time and estimate the amount of carbon currently stored in it. The approaches do not directly determine the permanence of the SOC, and changes in climate and management may modify current levels (Badgery et al., 2020). Hence, in most carbon sequestration schemes, current or future carbon levels eventually need to be monitored, reported, and verified (MRV) by measurements to demonstrate genuine abatement. The measurements associated with this process of MRV could be collected by farmers themselves or by an accredited organisation. The proposed field sampling will need to address both changes in bulk density and OCC and record any changes in land cover. Some authors have examined ways to reduce MRV costs through the potential of non-destructive soil carbon measurements such as in-field visible-near-infrared (vis-NIR) spectroscopic sensors and gamma-ray attenuation (England and Viscarra Rossel, 2018) and novel remote sensing techniques (Angelopoulou et al., 2019). In practice, a combination of approaches may be cost-effective.

## 5. Conclusion

In this study we have demonstrated our hypothesis that downscaling national-level soil C information to a farm and field level has different impacts depending on both the spatial modelling approach and the accounting method. From the three spatial modelling approaches to pay farmers for soil carbon sequestration, the models using fine-scale resolution input data appeared to provide a more robust estimate of the measured SOC than the one using coarse-scale input data. Additionally, the capacity of the fine input and output approach (Model 2) to pick up in-field variations could assist farmers in adjusting their management practices according to within-field variations in topography and soil type. The use of spatial models of SOC to predict the baseline for subsequent payments based on measured values of SOC tended to favour farms with high initial values of SOC, because the models tended to underestimate the SOC when the actual SOC was high. By contrast farms with initially low values of SOC tended to be unfavoured by the use of models to predict their initial baseline, as the models tended to predict SOC values close the actual values on such farms. Further research is recommended to compare the spatial modelling approaches with measured soil carbon values at depths greater than 10 cm and across different land covers as data become available. However, spatially explicit measured soil carbon and bulk density data from deeper depths are relatively rare.

## CRedit authorship contribution statement

**Styliani Beka:** Conceptualization, Methodology, Formal analysis, Data Curation, Writing-original draft, Visualization. **Paul J Burgess:** Conceptualization, Supervision, Project administration, Writing-Review & Editing, **Ron Corstanje:** Conceptualization, Supervision, Writing-Review & Editing, **Chris Stoate:** Writing-Review & Editing

Data underlying this study can be accessed through the Cranfield University repository at: <https://doi.org/10.17862/cranfield.rd.17877596.v1>.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2022.154164>.

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